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Secondary Forest Age and Tropical Forest Biomass Estimation Using TM

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ABSTRACT

The age of secondary forests in the Amazon will become more critical with respect to the estimation of biomass and carbon budgets as tropical forest conversion continues. Multitemporal Thematic Mapper data were used to develop land cover histories for a 33,000 km^2 area near Ariquemes, Rondônia over a 7 year period from 1989-1995. The age of the secondary forest, a surrogate for the amount of biomass (or carbon) stored above-ground, was found to be unimportant in terms of biomass budget error rates in a forested TM scene which had undergone a 20% conversion to nonforest/agricultural cover types. In such a situation, the 80% of the scene still covered by primary forest accounted for over 98% of the scene biomass. The difference between secondary forest biomass estimates developed with and without age information were inconsequential relative to the estimate of biomass for the entire scene. However, in futuristic scenarios where all of the primary forest has been converted to agriculture and secondary forest (55% and 42% resp.), the ability to age secondary forest becomes critical. Depending on biomass accumulation rate assumptions, scene biomass budget errors on the order of -10% to +30% are likely if the age of the secondary forests are not taken into account. Single-date TM imagery cannot be used to accurately age secondary forests into single-year classes. A neural network utilizing TM band 2 and three TM spectral-texture measures (bands 3 and 5) predicted secondary forest age over a range of 0-7 years with an RMSE of 1.59 years and an $R^2_{\text{actual vs predicted}} = 0.37$. A proposal is made, based on a literature review, to use satellite imagery to identify general secondary forest age groups which, within group, exhibit relatively constant biomass accumulation rates.

INTRODUCTION

The Brazilian Legal Amazon encompasses an area of approximately 5,000,000 km^2, stretching from the states of Maranhão and Tocantins in the east to Amazonas and Acre west, and from Roraima and Amapá in the north to Mato Grosso in the south. Approximately 4,090,000 km^2 of this area is forested, ~850,000 km^2 is cerrado (wooded grassland), and ~90,000 km^2 is water (Skole and Tucker, 1993; Fearnside, 1996). As of 1988, 230,324 km^2 , or 5.6%, of the ~4,090,000 km^2 forested Brazilian Legal Amazon had been deforested (Skole and Tucker, 1993; Skole et al., 1994) since colonization efforts began with the construction of the Belem-Brasilia Highway in 1958 (Moran et al., 1994). Each year approximately 15,000 - 20,000 km^2 of additional primary tropical forest are cut and cleared (Skole et al., 1994), though this yearly figure has varied greatly among studies and over the decades (~8,000-10,000 km^2 yr^{-1} in the 1970s, Mahar, 1988; ~35,000 km^2 yr^{-1} in the 1980s, Fearnside, 1989; ~15,200 km^2 yr^{-1} from 1978-1988, Skole and Tucker, 1993). A significant proportion of that deforested area cycles into and out of secondary forest regrowth from year to year (Fearnside, 1996; Alves and Skole, 1996), and this cycling has ramifications in terms of the carbon budget of the world's largest remaining tropical forest. The cutting , burning, and clearing of primary forest and the subsequent cycles of afforestation and deforestation affect the amount of carbon sequestered and released from a particular parcel of land over time. The rate at which carbon is sequestered by secondary forests depends on the age of the forest, the number of times that the land has been cleared and used for agricultural/pastoral purposes, land use while cleared (Uhl et al., 1988), soil fertility (Moran et al., 1994), and forest type (Houghton et al., 1991).

The overall objectives of this investigation are 1) to estimate the biomass and carbon budgets of an Amazonian area undergoing active colonization using multitemporal satellite data; 2) to determine if single-date Thematic Mapper imagery can be used to estimate the age and/or clearing history of a particular parcel of land; and 3) to estimate the size of the biomass budget errors involved with the use of single-date satellite imagery to describe land cover in a dynamic environment. Within objective #2, four specific subobjectives were identified: 2.1) to estimate classification accuracies associated with discrimination of primary forest, nonforest, and (collectively) all types of secondary forest; 2.2) to determine the accuracy with which the age of tropical secondary forest can be estimated using single-date TM multispectral and textural data; 2.3) to

determine if the clearing history of a particular tract of land (i.e., number of times cleared) can be ascertained spectrally; and 2.4) to compare the accuracies of secondary forest age determination using neural nets versus linear discriminant functions.

If satellite data can be used to measure secondary forest characteristics important to biomass cycling (i.e., areal extent, forest age, land use histories), then more accurate carbon budgets could be developed for the Amazon. Multitemporal Thematic Mapper digital satellite imagery acquired over an area surrounding the city of Ariquemes, Rondônia, Brazil in the southwestern Amazon (Figure 1) were analyzed to estimate the age of secondary forest regrowth. Clearing cycles were also documented to see if TM spectral data could be used to infer the number of times a particular parcel of land had been abandoned to secondary regrowth and then cleared again. Seven scenes acquired during the dry season from 1989 to 1995 were classified to identify primary forest, secondary forest, and nonforest/cleared areas. The seven forest classification maps were concatenated and used to develop land cover trajectories which identified a particular pixel as primary forest, nonforest, and secondary forest where each secondary forest pixel was identified by age of regrowth and number of times that the pixel had been cleared. This seven year data set served as the digital ground reference for this study.

BACKGROUND

The carbon dynamics associated with the ongoing transformation of the Amazon are globally significant. Brazil now ranks fourth in atmospheric carbon emissions (behind the United States (1), the former Soviet Block (2), and China (3); Goldemburg, 1989), due in large part to Amazonian deforestation (Moran et al., 1994). Though the general trend toward tropical forest loss in the Amazon is well documented (Setzer and Pereira, 1991; Fearnside, 1993; Skole and Tucker, 1993; Houghton, 1994 for an overview), there are more subtle but significant deforestation/afforestation issues that affect regional and subcontinental carbon budgets. Researchers who utilize satellite data to monitor deforestation are recognizing that secondary forests are an important component of Amazonian land cover change dynamics (Brown, 1993; Moran et al., 1994; Skole et al., 1994; Alves and Skole, 1996; Foody et al., 1996; Kimes et al., 1999a). Moran et al. (1994) provided an historical context to Amazonian development and deforestation. They made the point that rates of deforestation/afforestation in

the Amazon are responsive primarily to political and economic policies - federal tax incentives/subsidies for ranching, mining, logging - and only secondarily to population pressures. As an example, they also pointed out that, directly as a result of changes to these incentive/subsidy policies, pasture returning to forest accounted for the greatest area of all the man-modified land cover classes in the Altimira area (northern Pará) along the TransAmazon Highway.

Secondary forests are carbon sinks (Lugo and Brown, 1992). Tropical afforestation, i.e., the conversion of nonforested areas (pasture, cropland) to secondary forest, mitigates the net carbon flux to the atmosphere which results from timber harvesting. With respect to C sequestration rates[1], the amount of carbon sequestered by tropical secondary forests varies greatly. This variation is driven by age of the secondary forest, land use history of cleared area, number of times that the area has been cleared, soil fertility, and forest type. Houghton (1995, personal comm., see also Houghton et al. 1991) reported carbon accumulation rates of 5, 4, and 3 t C ha^{-1} yr^{-1} in tropical moist, seasonal, and open forests, respectively. He noted that carbon was also lost from the soil when forests were cleared and the land was cultivated. Houghton reported soil carbon uptake rates after abandonment of cleared areas of ~1.2, 1.2, and 0.85 t C ha^{-1} for tropical moist, seasonal, and open forests, resp. Uhl et al. (1988) studied 13 abandoned pastures near Altamira in northern Pará, Brazil. They established multiple (4-10) nested, fixed-area plots to estimate secondary forest biomass on cleared, then abandoned lands which had varied land use histories. They found that lightly-used pastures which reverted to forest (abandoned shortly after formation, light grazing) accumulated biomass - trees and vines - at a rate of approximately 10 t ha^{-1} yr^{-1}. After eight years, biomass had bounced back to 25% of original, primary forest levels. Moderately-used, abandoned pastures (grazing intensity ~1 animal unit/ha; used for 6-12 years as pasture) accumulated biomass at a rate of 5 t ha^{-1} yr^{-1}. The one, old, heavily-used site (moderate grazing pressure, used 6-13 years, mechanically cleared, disked, leveled) exhibited a biomass accumulation rate of 0.6 t ha^{-1} yr^{-1}. Uhl et al. (1988) noted that secondary forest age was a good predictor of biomass on lightly and moderately-used sites, but not on heavily-utilized sites. Lugo and

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[1] Fearnside (1996) used a carbon to biomass conversion factor of 0.45 for secondary forest, based on work by Guimarães (1993). In other words, the conversion of 100 tons of above-ground dry forest biomass is equivalent to 45 tons of carbon. He uses a conversion factor of 0.50 for primary forest, the same conversion factor suggested by Brown and Lugo (1984).

Brown (1982), in their Figure 2, provided another example of how quickly tropical moist forest accumulates biomass. Citing data from Bartholomew et al. (1953) working in the Belgian Congo, they illustrated a total biomass accumulation of 175 t ha^{-1} after 18 years, an average rate of 9.7 t ha^{-1} yr^{-1} over that period. [The growth rates over that 18 year period were not linear. Rates varies from ~18.75 t ha^{-1} yr^{-1} for the first 8 years to 2.5 t ha^{-1} yr^{-1} over years 9-18.] Given that undisturbed tropical moist forests on average maintain 223 - 538 t ha^{-1} (Brown and Lugo, 1980), this recovery represents 33% - 78% of predisturbance, total forest biomass values in less than 20 years. Harmon et al. (1990) reported that, although secondary forests are carbon sinks, the conversion of primary forest to young, fast-growing secondary forest results in a net CO_2 flux to the atmosphere, even when carbon sequestration in buildings is taken into account. The creation of rapidly growing secondary forests from primary forests will not reduce net, long-term, atmospheric CO_2. However, given that significant areas of primary forest have already been cleared, conversion of lands to permanent agriculture should be met, as much as possible, from secondary forests since secondary forest C pools are smaller than primary forest (Brown, 1993).

Secondary forests which arise from cleared areas are an important land cover component in the Amazon, especially along the eastern and southern edges of the Legal Amazon where most of the clearing activities take place. Alves and Skole (1996) documented cover type transitions in Rondônia over a six year period from 1986 to 1992. On their 210,884 ha study area they found that the total area deforested increased from approximately 29,000 to 47,000 hectares over 6 years, a conversion rate of ~1.5% yr^{-1} [2]. Depending on the year, anywhere from 22 to 48% of the total area altered by man was in secondary forest. They concluded that both abandonment of cleared areas and the clearing of secondary forests are common and important practices in this particular area. Fearnside (1996) used Markov matrix analysis to quantitatively describe future Amazonian land cover based on ranching/farming landscapes and associated transition probabilities in Rondônia (Skole et al., 1994) and northern Pará (Moran et al., 1994). The objective of his study was to realistically model equilibrium land cover transitions in areas where the primary forest has already been cleared in

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2 This clearing rate is unusually high and is characteristic of an area undergoing active colonization. Skole and Tucker (1993) report a clearing rate of 0.74% for Rondônia (1978-1988). INPE (1992, as cited in Alves and Skole, 1996) record clearing rates for Rondônia of 0.9% (1978-1989), 0.6% (1988-1991), and 0.4% (1990-1991).

order to more accurately assess carbon fluxes of converted Amazonian landscapes. His study did not address primary forest conversion; rather it attempted to characterize, at least to a first order, farmland/pasture - secondary forest interactions. In regions where farmers utilize/control 30% of the area and ranchers control 70%, the equilibrium landscape in the year 2090 would be composed of 4% farmland, 44% productive pasture, 5% degraded pasture, and 47% secondary forest. Fearnside calculated that approximately 14% of the productive pasture, 7% of the degraded pasture, and 8% of the farmland would transition to secondary forest each year. On average, farmland would be actively worked for 1.8 years prior to transition to another land use. Secondary forest residence times would be on the order of 5 - 6 years after which they would revert to farmland or pasture (Fearnside, 1996, Table 3C). [Skole et al. (1994) has reported a mean turnover time for secondary forest of 5 years in the Ariquemes, Rondônia area.] It is obvious from Fearnside's transition matrix that secondary forests play a key role in conversion areas. The role of secondary forests in carbon flux and biomass calculations will only become larger as more of the Amazon is cleared.

Earth satellite data can be used to differentiate secondary forests from primary forests and nonforested areas in the tropics. Steininger (1996), using TM digital data, found that primary and secondary tropical forest spectral signatures were distinct up to approximately the 14 year mark. Older secondary forest (>13 years) became more and more spectrally inseparable as the regrowth aged. Moran et al. (1994) successfully differentiated 3 classes of secondary regrowth from nonforest and primary forest in the eastern Amazon. Field investigations near Altimira on the TransAmazon Highway identified secondary regrowth 1-5 years old (yo), 6-10 yo, and 11-15 yo. These three classes, along with primary forest and nonforest classes, were identified at individual class accuracies exceeding 92% using TM data. Like Steininger, they concluded that, at least in areas of fertile soil, at "15 years..., the difference in reflectance seems to be getting close to mature forest...". Foody et al. (1996) differentiated six clearing classes (pasture, <2 yo, 2-3, 3-6, 6-14, and >14 yo) near Manaus, Brazil with class accuracies of 99.3, 34.6, 81.7, 53.1, 72.7, and 97.7% respectively. As expected, adjacent age classes were the source of most classification confusion. Kimes et al. (1999a) looked at an eight-year multitemporal composite of multispectral, 20m SPOT data near Ariquemes, Rondônia. Using one-date (1994, the most recent date in the composite) SPOT spectral data and texture data, they

discriminated primary forest, nonforest, and secondary forest at individual class accuracies of 96.0, 99.7, and 89.9% respectively. They also concluded that the specific age of the secondary forest (e.g., 1 yo, 2 yo, etc.) could not be reliably estimated using single-date SPOT multispectral and texture data.

PROCEDURE

Landsat-5 TM scenes were acquired over a seven year period from 1989 to 1995. The seven TM scenes analyzed in this study include the following acquisition dates for path 232, row 67: July 8, 1989, December 2, 1990, June 12, 1991, June 22, 1992, October 7, 1993, June 4, 1994, and July 25, 1995. Since there were no gaps in this yearly record, temporal gap errors such as those discussed by Kimes et al. (1998) were not of concern. The majority of the scenes were acquired during the southern winter dry season - June through September. Only six of the seven TM bands were utilized from each scene; band 6, the thermal band, was not considered due to its 120m spatial resolution. All images were registered to the June 22, 1992 image. RMS registration errors in the along- and across-track directions ranged from 0.4 to 0.7 pixels. RMS total registration errors ranged from 0.75 to 0.95 pixels.

Each of the seven scenes was independently classified into six cover types - primary forest (p), nonforest/cleared (n), secondary forest (s), natural nonforest (g), obscured (o, i.e., cloud, cloud shadow), and water (w) using an unsupervised classification approach. Secondary forest was defined as those areas abandoned after the forest vegetation had been removed. Abandonment was defined as per Fearnside (1996), i.e., years since the last burning. The majority of the TM acquisitions were dry season acquisitions where areas burned in the current year were spectrally distinct from unmanaged areas. It is noted that this definition and this study's dependence on spectral separability between areas burned in the current year and areas abandoned for 1 or 2 years is a potential source of error. However, the rapid biomass accumulations noted on many abandoned tropical forest lands (Lugo and Brown, 1982; Uhl et al., 1988, Houghton et al., 1991) mitigate the size of the error. Accuracy assessments done on similar TM level 1 classification products have reported class accuracies over 90% given the simplistic, spectrally distinct cover types being differentiated (Moran et al., 1994; Coppin and Bauer, 1996; Kimes et al., 1999a). The seven digital classifications, i.e., the 1989 through 1995 land cover maps, were

concatenated. The area common to all seven scenes incorporated 36,671,865 pixels, an area of approximately 33,000 km^2.

The seven concatenated classifications formed a 7 band image of land cover trajectories. A mapping program was developed which evaluated the tens of thousands of possible land cover trajectories to produce an output image containing the 21 classes listed in Table 1. Of particular interest were the identities of secondary forest with respect to age and clearing history based on 1989-1995 land cover classifications.

Based on the seven year trajectories, the secondary forest in the output image was identified according to the number of times that the particular area had been cleared and according to its age since abandonment. The number of times cleared is referred to as "degree" in this report. First degree areas were those which had been cleared only once within the available TM record. Second degree secondary forest had been cleared twice between 1989 and 1995. As an example, a seven date trajectory for a particular pixel might be "ppnsnss", i.e., this pixel was classified as primary forest in 1989 and 1990, nonforest in 1991, secondary forest in 1992, cleared again in 1993, and grew into secondary forest in 1994 and 1995. This pixel would be identified in the output image as 2° - 2 yo secondary forest in 1995. The rules used to map the different combinations of land cover types over 7 years to one of 21 land cover classes are reviewed below.

General Mapping Rules:

1. A pixel obscured in any two or more years or one obscured in 1995 was "obscured" in the output image.
2. A pixel classified as water in any date was identified as water in 1995.
3. A pixel classified as natural nonforest in any date was identified as natural nonforest in 1995.
4. Primary forest could not follow nonforest, such a pixel remained "unclassified", ex. ppnnnpp.
5. Primary forest could follow secondary forest. This rule permitted consideration of situations where secondary forest might, over time, become spectrally indistinquishable from primary forest. Ex. pnnsssp would be classified as 1st degree, 4 yo secondary forest in the output image; pnsnspp as 2°, 3 yo secondary forest.

6. Secondary forest could not follow primary forest. Any trajectory with a "...ps.." in it remained "unclassified". Forest clearing had to be seen and was not assumed.
7. Any trajectory containing the sequences "..nos.." or "..nop.." were identified as "unclassified" in the output image. Though these sequences were certainly plausible, the obscured year called into question the age of the secondary forest (..nos..) or the possible validity (..nop..) of the trajectory.
8. Any trajectory containing the sequences "..non.." or "..sos.." were "unclassified" since the obscured year called into question the degree of clearing, e.g., cleared once, cleared twice.
9. Any trajectory containing the sequence ".spos.." were "unclassified" though the trajectory was quite possibly valid. In order to accurately age secondary forest, a decision was made that the clearing had to be seen, it could not be assumed.
10. Any trajectory which was obscured in 1989 was "unclassified" since the obscured year called into question the age and degree of secondary forest.

This mapping program was developed primarily to insure that the different secondary forest age classes were identified as accurately as possible. It was not developed to maximize the overall accuracy of the 21 class output image. It should be noted that these rules tend to overestimate the area of water and natural nonforest and the rules tend to place a significant number of potentially useful pixels into an "unclassified" category. These inaccuracies were knowingly exchanged for a more accurate and unambiguous set of potential secondary forest training and test areas. Also, the land area represented by these unclassified pixels were later apportioned to the different land cover classes based on a visual inspection of a sample of these unclassified pixels.

This 21 class image contained the location of primary forest, nonforest, and 16 secondary forest classes in the 1995 TM image. Each of these classes was screened to identify areas to train and test linear discriminant and neural net functions. Given that there was misregistration error between scenes (up to 0.95 pixels RMS worst case), to the extent possible polygons outlining training and test sites were located within (i.e., away from the edges of) contiguous areas identified as a single class.

Having selected training and test samples for the neural net and linear discriminant functions, attention was turned to apportioning those pixels which had been identified as unclassified. Approximately 4.4% of the TM scene pixels

were unclassified. These pixels represented a "nonsense" class, a class of trajectories which did not make sense given the trajectory mapping rules provided. These pixels were studied to determine why almost one-twentieth of the scene was considered nonsensical. The vast majority of these pixels were associated with secondary forest. A 0.025% systematic subsample (n = 405) of these unclassified pixels were selected and visually categorized so that the unclassified pixels could be partitioned amongst the primary forest, nonforest, and secondary forest cover types to facilitate biomass calculations. Approximately half of this unclassified group lay on clearing edges and, due to small misregistration errors, flipped back and forth between nonforest or secondary forest and primary forest (a violation of rules 4 or 6). Other areas seemed to have been selectively logged or thinned and never went through a cleared or nonforested state. Of the 405 pixels checked, 36.3% were primary forest in 1995, 2.7% were nonforest, 61.0% fell into one of the secondary forest classes. The area associated with the 1.6+ million unclassified pixels was apportioned into the 21 land cover classes for biomass budget calculations based on proportions calculated from this sample. Cover class percentages (after apportionment) for the area surrounding Ariquemes, Rondônia are reported in Table 1.

In order to investigate the spectral separabilities and the map accuracies associated with the land cover classes listed in Table 1, training and test areas were identified in the 1995 TM image. Interior polygons, i.e., polygons away from clearing edges, were delineated in primary forest, nonforest, and in 15 of the 16 secondary forest classes. The fourth degree, one year old secondary forest class was not considered due to its limited and widely scattered extent. For each of the 17 cover types, a list of all pixels included in these interior polygons was compiled. Each list was systematically sampled to develop files with equal class sizes for use in subsequent analyses. This approach ensured that responses across the entire image were selected, it ensured that only a few pixels from each polygon were sampled, and it resulted in equal weighting (i.e., class sizes) for each of the 17 land cover types considered. The pixel lists included pixel location, class assignment, the six TM spectral responses, and 13 digital texture measures. The texture measures, derived using a 3x3 moving window on TM bands 3, 4, and 5 (red, near infrared, and short wave infrared wavelengths), were included in the lists based on the results of preliminary linear discriminant and

neural net variable selection analyses, and based on work by Kimes et al. (1999a). The specific texture measures utilized are available from the primary author.

These spectral/textural response lists were used 1) to estimate classification accuracies associated with discrimination of primary forest, nonforest, and (collectively) all types of secondary forest; 2) to determine the accuracy with which the age of tropical secondary forest can be estimated using TM multispectral and/or textural data; 3) to determine if the clearing history of a particular tract of land (i.e., number of times cleared) could be ascertained spectrally; and 4) to compare the accuracies of secondary forest age determination using neural nets (Kimes et al., 1999b) versus linear discriminant functions.

The results of these accuracy assessments were then used to estimate biomass and carbon budget errors involved with the use of single-date TM imagery to assess secondary forest. Error rates were calculated for the present day situation in the Ariquemes, Rondônia area as typified by the trajectory history as of 1995. Budget errors for biomass and carbon were also calculated for a future landscape as described by Fearnside (1996) in which the predominant land covers are agriculture, pasture, and secondary forest.

RESULTS

Biomass budget of an Amazonian area undergoing active colonization

As noted in Table 1, almost 80% of this Landsat scene is primary forest. As noted in Table 2, over 98 percent of the biomass and carbon in this scene in 1995 was invested in these primary forests. Table 2 reports the biomass and carbon allocations to the various cover types as described using the 7-date trajectory composite.

Given that all of the secondary forest, nonforest, and the majority of the water areas were originally primary forest, a coarse estimate of biomass flux and carbon flux for this area can be calculated. Since the early 1970's when BR-364 was built and colonization begun (Frohn et al., 1996), 633,083 ha have been cleared or inundated. At an average biomass of 372 t/ha, 235.7 million tons of biomass were cut, releasing 117.8 million tons of carbon over this 25 year period. The cleared areas in this time frame have accumulated carbon, specifically those amounts reported in Table 2 - 13.5 million tons of above-ground dry biomass, or 6.1 million tons of carbon. This specific 33,000 km^2 area surrounding and west of Ariquemes, Rondônia, then, has released approximately

4.5 million tons of carbon/year from approximately 8.9 million tons of forest biomass/year. The carbon flux rate for this 33,000 km^2 area over the 25 year period prior to 1995 was 1.34 t C ha^{-1} yr^{-1} released to the atmosphere; the biomass loss rate was 2.69 t biomass ha^{-1} yr^{-1}. These figures are approximate, specific to the area of the 1995 TM scene, and do not take into account soil carbon pools. Houghton et al. (1991) reports that below-ground biomass may be calculated as approximately 25% of the above-ground biomass, though the soil biomass is extremely variable, i.e., 8 to 85% of the above-ground amount.

The estimates developed thus far were based on the individual classifications of and trajectory analysis of seven TM scenes acquired from 1989 to 1995. Such multitemporal data sets are atypical and labor intensive. An investigation was undertaken to determine if forest status (i.e., primary, secondary), age, and/or cutting history (e.g., first degree, second degree) could be determined using single-date Thematic Mapper imagery.

TM imagery to estimate secondary forest age and clearing history

A) Determining secondary forest age using TM

Numerous linear discriminant and neural net analyses were conducted to quantify accuracies associated with the use of TM spectral and/or textural data for differentiating primary forest from nonforest from secondary forest. Table 3 lists test accuracies for the three cover types for the linear discriminant functions and neural nets. The results in Table 3 document the facts that 1) all three cover types (where the third cover type included all of the different secondary forest degree and age classes) were differentiated at accuracies exceeding 90%; 2) the use of textural information increased classification accuracies 1-3 percentage points; and 3) neural nets, using fewer input spectral and textural bands, consistently (with few exceptions) outperformed linear discriminant functions by 1-3 percentage points. The results of these analyses were very similar to those found in a previous investigation (Kimes et al., 1999a) which considered the use of SPOT-HRV data for tropical secondary forest assessment.

A second set of LD and NN functions were developed to determine how well secondary forest could be differentiated from primary forest as the secondary forest aged. The neural net results are presented in Figure 2. The linear discriminant results are not given since the individual class accuracies are

consistently 1-2% lower and since the trends are identical[3]. In these analyses, an LD function or a neural net was developed which differentiated primary forest from, collectively, all of the secondary forest cover classes. The LD function or neural net was then applied to each of the secondary forest classes individually to determine 1) if accuracies tailed off as the secondary forest aged (and began to "look" more and more like primary forest); and 2) if secondary forest age classes with different clearing histories (different degrees) were classified any more or less accurately. As seen in Figure 2, classification accuracies, though somewhat variable, do not decrease with increasing forest age, at least within the range of ages considered in this study. These results support findings by Moran et al. (1994) and Steininger (1996) who concluded that secondary forest up to the age of ~15 years can be reliably differentiated from primary forest using satellite data. As expected, Figure 2 also indicates that forest growing on lands which have been cleared multiple times are as easily if not more easily differentiated from primary forest.

Finally, attempts were made to estimate secondary forest age directly using multiple linear regression and neural net techniques using single-date (1995) TM imagery. As in the previous analyses, the neural net results were marginally more accurate that the LD results. As such, only the NN figures are reported here. Considering the spectral data only, the neural net utilized all six TM bands and constructed a $6 \rightarrow 12 \rightarrow 1$ network. The RMSE of predicted age was 1.67 years, with an actual versus predicted age R^2 value of 0.29. Figure 3 illustrates the actual versus predicted age relationship when a neural net was constructed using TM spectral and textural information. A $4 \rightarrow 11 \rightarrow 1$ network utilizing TM2, and three texture measures produced an RMSE of 1.59 years with an R^2 of 0.37. As noted in Figure 3, the nonlinear prediction network yields highly variable estimates of age (as does the linear function, RMSE 1.62 years, R^2 of 0.35) which, from a practical standpoint, is of little utility for predicting secondary forest age.

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[3] Stepwise discriminant analysis was conducted to identify the spectral and textural band combination most useful for linearly discriminating primary forest from the combined collection of all secondary forest age classes. The best six bands included TM7 and 5 texture measures, including the 3x3 moving averages of TM 3, 4, and 5. These and other band selection results confirm Boyd et al.'s (1996) finding that the Landsat TM middle infrared bands (TM5 and 7) are especially useful for "discrimination of different regeneration stages in tropical forests".

B) Determining clearing history using TM

Spectrally, secondary forest age and clearing history are confounded. As noted by Uhl et al. (1988), secondary forests which have been repeatedly cleared and used for crops or pasture recover more slowly. Hence older second and third degree forests will appear to be similar to younger first degree forests. Figure 4 illustrates the spectral similarities of secondary forests with different clearing histories. Not shown in Figure 4 (in the interest of clarity) are the spectral variances associated with the plotted mean values. One standard deviation plotted around any of the three "degree" means would incorporate the means of the remaining two groups. First, second, and third degree secondary forests are very similar spectrally, and worse, age is confounded with clearing history insofar as younger first degree secondary forest is spectrally similar to older second and third degree secondary forest. Information concerning clearing history cannot be reliably deduced using single-date TM imagery.

C) Biomass Budget Errors using TM data

The purpose of this portion of the investigation was to determine the sizes of errors which might be incurred with respect to determining standing biomass given single-date satellite imagery and an inability to classify secondary forest into age classes. The reader should understand that biomass budgets and budget errors are directly proportional to estimates of carbon - see footnote 1. As noted above, single-date TM imagery could not be used in this study to reliably, accurately estimate secondary forest age. Two Rondônian scenarios were evaluated to determine coarse biomass budget estimation errors that might be encountered if scientists have only single-date satellite imagery available. Implicit in the use of single-date TM imagery is that secondary forest must be monolithically classified. The first scenario looked at a present-day (i.e., 1995) scenario where, as is the case near Ariquemes, approximately 20% of the Landsat TM scene has been converted from primary forest into cleared or secondary forest areas. In the first case, the biomass budget presented in Table 2 was used as ground reference, i.e., the best estimate available of what was actually on the ground near Ariquemes in 1995. The first scenario compared the biomass budget calculated using the trajectory information (with forest ages and clearing history) versus that same scene where secondary forest was identified only as a single class (due to the limitations imposed by our inability to accurately discern the age of the regrowth).

The second scenario considered a futuristic Rondônian landscape in equilibrium, one which has reached an areal stasis as calculated by Fearnside (1996). Looking into the future 100 years using Markov chains, Fearnside described land cover areas and transitions between the different land cover types for an Amazonian tropical forest area which has undergone extensive, longterm forest conversion. Using Fearnside's enumeration of different agricultural and secondary forest areas, biomass budgets were calculated with and without secondary forest age information. These biomass budgets were compared to describe errors which might be incurred if secondary forest age was not taken into account in a landscape dominated by forest conversion.

<u>Scenario 1 - Present Day, 1995</u>:

Scenario 1 looks at an situation where approximately 20% of the primary seasonal tropical forest has been converted to agriculture and secondary forest. Biomass estimates were calculated assuming that secondary forest age classes could not be differentiated. Two different secondary forest regeneration rates were assumed for the monolithic, undifferentiated secondary forest class, 5 and 10 t biomass ha^{-1} yr^{-1} (Uhl et al, 1988). It was also assumed that secondary forest was, on average, 5 years old (Skole et al., 1994; Fearnside, 1996). The areal estimates in Table 2 were used in conjunction with these growth and age assumptions to calculate biomass for converted forest and for the entire 33,000 km^2 TM scene.

The results indicated that, without age information, secondary forest biomass errors of approximately -20% (5 t ha^{-1} yr^{-1}, 5 yo) to 60% (10 t ha^{-1} yr^{-1}, 5 yo) were incurred. These percentage differences were relative to the "true" secondary forest biomass calculated as a function of age in Table 2 (i.e., 6,795 t). However, relative to the entire TM scene, differences between the total scene biomass computed with and without age information were less than half of one percent. In other words, if one is interested in estimating the biomass of secondary forest in and of itself, age information is crucial. The lack of that information can lead to substantial errors which themselves depend on assumptions made concerning the average age and accumulation rates of the secondary forest. However, if one is interested in calculating the biomass over an entire TM scene where approximately one-fifth of that scene has been converted, secondary forest age information is almost inconsequential. Such a finding is understandable in light of the fact that approximately 80% of the area

is in primary forest and this cover type supports the vast preponderance of the above-ground biomass.

In an area such as Rondônia, with time, the extent of primary forest will dwindle and the area of secondary forest will increase. Biomass (and carbon) budget errors will obviously become more pronounced as the areal extent of secondary forest grows relative to primary forest area. A second scenario is studied to quantify the importance of secondary forest age information in a situation where all of the original forest has been cut.

<u>Scenario 2 - ~100 years in the Future, 2090:</u>

Scenario 2 looks at a situation where effectively 100% of the primary forest within a TM scene has been converted to agricultural uses or secondary forest. Fearnside (1996) predicted that a colonization area will, in the year 2090, be composed of 0.9% primary forest, 56.4% nonforest/agriculture, and 42.7% secondary forest. His primary forest was actually described as secondary forest >100 years old, effectively carrying the same amount of biomass as the primary forest. His nonforest/ag areas were predicted to be composed of farmland - 5.2%, productive pasture - 46.8%, and degraded pasture - 4.4%. 2.2% of the secondary forest lands were predicted to come from farmland, 40.5% from pasture. These percentages were combined with the characteristics of the Rondônia TM scene in 1995 to characterize the scene in 100 years. This characterization is presented in Table 4. In producing Table 4, it was assumed that 1) the area of water and natural nonforest did not change over the 100 years; and 2) the age-class breakdown of the secondary forest was identical to the 1995 scene. These assumptions are certainly arguable but are relatively unimportant. The important point is that the land cover breakdown described in Table 4 is a scientifically credible description of one possible future condition.

As noted in Table 4, young (<8 yo) secondary forest accounted for over 40% of the land area in this futuristic scene, and almost 50% of the scene biomass resided in this young secondary forest. An additional 12% of the biomass resided in very old secondary forest (>100 y.o.). Obviously, as any colonization/settlement area ages, secondary forest will play a larger role in biomass and carbon state and flux measurements. The question addressed here is "What errors are involved in biomass estimates if secondary forest age information is not available?". With Table 4 describing a colonization endgame and it's biomass estimates serving as ground reference, alternate biomass estimates were generated without the age/clearing history. As in scenario 1, it

was assumed that the undifferentiated secondary forest class was, on average 5 year old and accumulated biomass at two different rates, 5 and 10 t ha^{-1} yr^{-1}.

Since the same age/clearing history breakdowns were used in the 1995 and 2090 scenarios, the error rates associated with estimating secondary forest biomass were identical (5 t ha^{-1} yr^{-1} yielded a 19% underestimate; 10 t ha^{-1} yr^{-1} yielded a 62% overestimate). However, since secondary forest made up such a large areal percentage of the scene and carried the majority of the biomass, errors associated with scene biomass estimates were much larger than in the 1995 scenario. An accumulation rate assumption of 5 t ha^{-1} yr^{-1} yielded a scene biomass error rate of -9%; an accumulation rate of 10 t ha^{-1} yr^{-1} resulted in a 30% biomass overestimate for the entire scene. These are markedly distinct from the error rates of less than one-half percent noted in 1995.

The important point to be made here is that, as forest conversion continues and as secondary forest becomes the majority cover type with respect to scene biomass, the age and clearing history of that forest will become more important from the standpoint of biomass and carbon state measurements. The numbers presented here are coarse approximations. The same assumptions concerning biomass accumulation rates were used to generate both the ground reference data (with age data) and the undifferentiated (without age data) secondary forest biomass estimates. Similarities were maintained so as not to inflate estimation errors, and the authors recognize that these similarities introduce some circularity to the case being made. However, the purpose of the investigation was to quantify the impact of secondary forest age information (or lack of that information) on the biomass and carbon budgets of a tropical forest undergoing conversion. The findings indicate that secondary forest age information is crucial to developing accurate estimates of biomass and carbon 1) in secondary forests (without concern for other cover types); or 2) in those situations where the majority of the biomass in a given study area rests in secondary forest. The study also indicates that single-date Landsat TM data can be used to accurately and reliably delineate secondary forest from primary forest and nonforest. However, single-date TM spectral and textural data cannot be used to classify secondary forest age into one year age groups, and it cannot provide insight into clearing history. The comparisons provide estimates of errors which might be incurred if secondary forest age information is not available. Scene biomass estimation errors on the order of -10 to +30% were noted in the situation where

secondary forest age information was not available and where the region was dominated by nonforest and secondary forest cover types.

CONCLUSIONS

Many previous studies which have quantified the effects of Amazonian deforestation in terms of biomass or carbon flux have done so assuming a monolithic transformation from forest to pasture or from forest to bare ground. The replacement, nonforest cover type is assumed to remain in that state indefinitely. This simplistic assumption leads to biomass estimation errors and hence carbon state and flux errors since the effects of secondary forest in terms of biomass accumulation and storage are completely ignored (Fearnside, 1996). Any adequate treatment of biomass and carbon in the Amazon 1) will have to include secondary forests in the budget; and 2) should, if possible, consider at least the age of the secondary forest in calulating biomass. With time, as more land is cleared, biomass estimation errors will increase. Even if secondary forest land cover is taken into account, biomass estimation errors on the order of 30% may be realized if the age structure of the secondary forest is not taken into account.

The results of this study indicate that single-date TM imagery could not reliably, accurately discriminate secondary forest age based on TM spectral and texture data. However, other studies have successfully delineated broader age categories (e.g., 1-5, 6-10, 10-15 yo - Moran et al., 1994; 1-5, 5-8 yo - Rignot et al., 1997) and numerous studies agree that secondary forest and primary forest satellite spectral signals merge after approximately 15 years (Moran et al., 1994; Foody et al., 1996; Steininger, 1996). There is evidence that tropical forest accumulation rates are relatively constant between 1-10 years old and then drop off significantly (Lugo and Brown, 1982; Brown and Lugo, 1990). A simple division of secondary forest into broad age categories (e.g., Moran's categories, 1-5, 6-10, 11-15 yo) and the application of general biomass accumulation rates may go a long way to mitigating estimation errors. At this point, there is not a consensus in the literature as to what biomass accumulation rates might be assigned to these general age categories. In fact, regeneration rates vary widely (see Lugo and Brown, 1982; Salati and Vose, 1983; Uhl et al. 1988; Brown and Lugo, 1990; Moran et al., 1994; Rignot et al. 1997 for a range of estimates). The authors suggest, based on their literature search, that the following rates might provide reasonable midpoints: 10 t above-ground dry

biomass $ha^{-1} yr^{-1}$ from 1-5 yo and 6-10 yo (a composite estimate based on Uhl et al., 1988; Brown and Lugo, 1990; Houghton et al., 1991; and Moran et al. 1994), and 4 t $ha^{-1} yr^{-1}$ from 11-15 yo (Brown and Lugo, 1990, extracted from Foody et al., 1996, Fig. 1). Although this study indicates that TM data cannot be used to exactly age secondary tropical forest, studies by others indicate that age groups can be characterized, especially if multispectral satellite data are considered in conjunction with relatively long-wavelength (e.g., L-band) cross-polarized satellite or shuttle radar returns (Saatchi et al., 1997; Yanasse et al., 1997; Rignot et al., 1997) or if multitemporal satellite spectral and texture data are utilized (Kimes et al., 1999a).

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Table 1. Area of each of the 21 cover classes based on seven year land cover trajectories, 1989-1995. All land cover classes, including secondary forest ages and clearing histories, are relative to the conditions present in the 1995 TM scene. Areas were calculated based on a 30m x 30m TM pixel.

class	area (ha)	%	area (ha)	%
primary forest			2,589,063	78.4
nonforest/cleared			402,130	12.2
water			11,421	0.3
obscured/clouds †			17,134	0.5
natural nonforest			61,188	1.9
secondary forest, 1st degree				
1 year old	34,213	1.0		
2 years old	25,645	0.8		
3 years old	23,442	0.7		
4 years old	10,101	0.3		
5 years old	20,205	0.6		
6 years old	8,283	0.3		
7^+ years old	36,613	1.1		
total, 1° sec. for.			158,503	4.8
secondary forest, 2nd degree				
1 years old	11,763	0.4		
2 years old	18,479	0.6		
3 years old	7,379	0.2		
4 years old	3,612	0.1		
5 years old	9,534	0.3		
total, 2° sec. for.			50,768	1.5
secondary forest, 3rd degree				
1 years old	2,655	0.1		
2 years old	5,930	0.2		
3 years old	1,561	~0		
total, 3° sec. for.			10,146	0.3
secondary forest, 4th degree				
1 year old	117	~0		
total, 4° sec. for.			117	~0
Total:			3,300,468	100.0

† Two or more dates obscured by clouds/cloud shadow and/or 1995 obscured.

Table 2. Total above-ground dry biomass and carbon budgets for the 1995 Landsat TM scene.

class	biomass t/ha	area(ha)	t biom. x 10^3	t C x 10^3	C (%)
primary forest	372 [1]	2,589,063	963,779	481,889 [2]	98.4
nonforest/cleared	17 [3]	402,130	6,695	3013 [4]	0.6
water	0	11,421	0	0	0
obscured/clouds	-	17,134	-	-	-
natural nonforest	50 [5]	61,188	3,059	1530 [2]	0.3
secondary forest					
1st deg.	38 [6]	158,503	6,033	2715 [4]	0.6
2nd deg.	13 [7]	50,768	665	299 [4]	0.1
3rd, 4th deg.	9 [7]	10,262	97	44 [4]	~0
Total		3,300,468	980,327	489,490	100

[1] The primary forest biomass estimate is an average of two ranges: 223 - 538 tons/ha for tropical moist forest (Lugo and Brown, 1982), and 292 - 436 tons/ha for Rondônia (Rignot et al., 1997).
[2] Biomass to carbon conversion factor of 0.5 used.
[3] The nonforest biomass estimate is an average of carbon accumulation estimates from Houghton et al. (1991), recalculated as dry biomass using Guimarães' (1993) and Fearnside's (1996) carbon to biomass conversion factor of 0.45. Houghton et al. (1991) estimates that croplands maintain 5 tC/ha and pastures 10 tC/ha, which is equivalent to 11.1 and 22.2 t biomass/ha resp. Assuming an equal split between cropped and grazed areas in this 1995 scene, the nonforest areas maintain 16.7 t biomass/ha, on average.
[4] Biomass to carbon conversion factor of 0.45 used.
[5] Natural nonforest was assumed to maintain approx. 50 t biomass/ha.
[6] First degree secondary forest was assumed to accumulate dry biomass at a rate of 10 t ha^{-1} yr^{-1} (Uhl et al., 1988, "lightly" used cleared areas).
[7] Second, third and fourth degree secondary forest was assumed to accumulate dry biomass at a rate of 5 t ha^{-1} yr^{-1} (Uhl et al., 1988, "moderately" used cleared areas). The actual accumulation rates reported in the table are weighted by the age and area of the different secondary forest cover types.

Table 3. Linear discriminant (LD) and neural net (NN) test classification accuracies - primary forest versus nonforest versus all (combined) secondary forest classes. 3000 pixels in each of the three general forest cover classes were used to train the LD and NN functions; a second 3000 pixels in each class were used to estimate test accuracies. All table entries are in percent.

Band Combination	Classifier	primary forest	non-forest	secondary forest	overall accuracy [1]
6 TM bands	LD	92.7	94.8	90.5	92.7
	NN [2]	95.4	97.6	92.6	95.2
13 texture ch.	LD	97.8	97.5	93.0	96.1
	NN [3]	98.9	98.8	97.8	98.5
6 TM + 13 text.	LD	98.6	97.6	94.1	96.8
	NN [4]	98.7	96.5	96.3	97.2

[1] Since class sizes are equal, average (class) accuracy equals overall (per pixel) accuracy. In the parlance of user - producer accuracies, these are producer accuracies.

[2] The neural net used three of the six TM bands available (TM 3, 4, and 5) in a $3 \rightarrow 6 \rightarrow 3$ network - 3 inputs, 6 hidden nodes, 3 outputs.

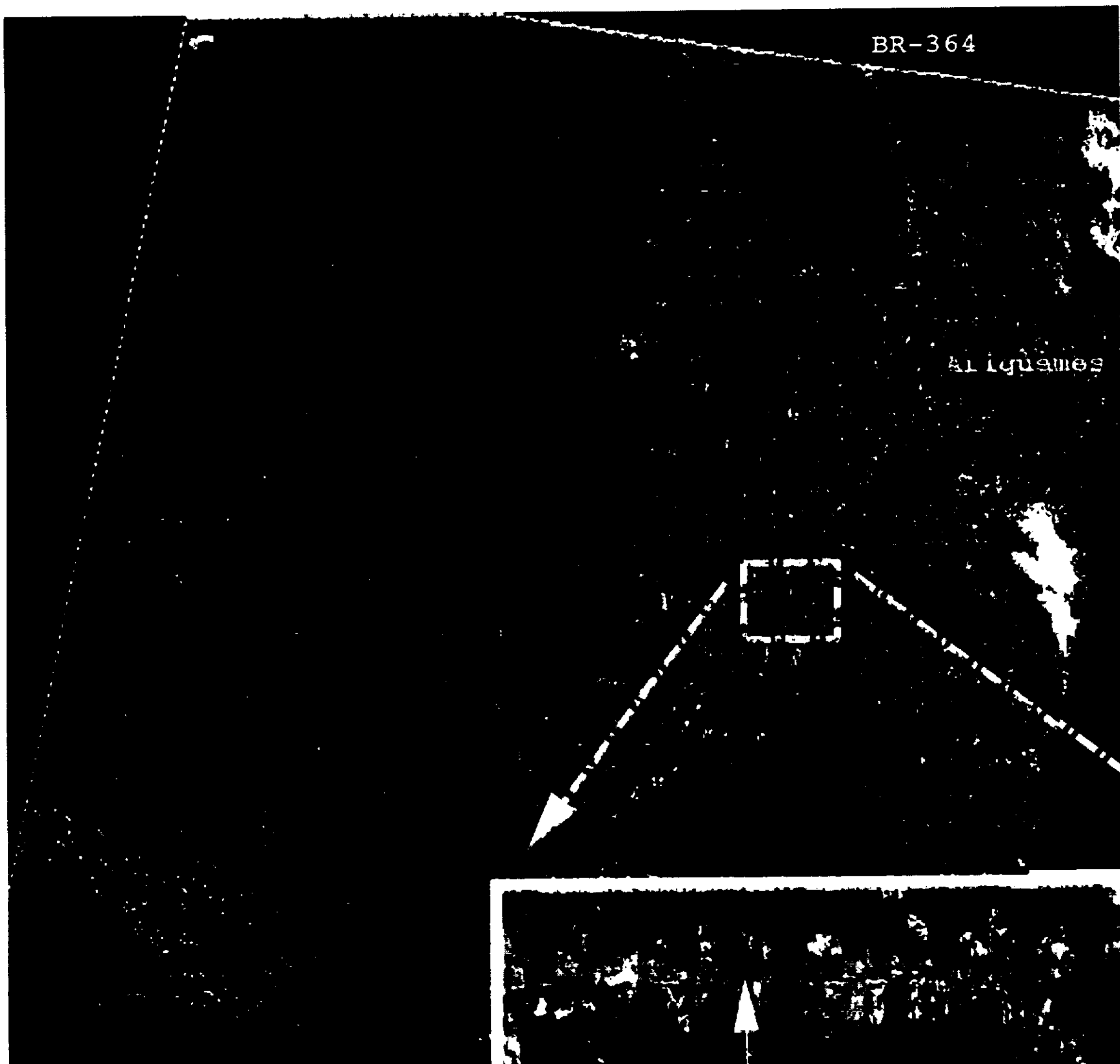
[3] The neural net used six texture bands derived from TM bands 3, 4, and 5 in a $6 \rightarrow 4 \rightarrow 3$ network.

[4] The neural net used three of the 19 spectral and texture bands available (TM2, a TM3 mean texture measure, and a TM5 variance measure) in a $3 \rightarrow 3 \rightarrow 3$ network.

Table 4. Land cover area and biomass for the TM scene in the year 2090.

class	biomass (t/ha)	area (ha)	areal %	t biom .x 10^3	biom. %
primary forest	372	29,051	0.9	10,814.2	12.5
nonforest/cleared	17	1,820,513	55.2	30,402.6	35.0
water	0	11,421	0.3	0	0
natural nonforest	50	61,688	1.9	3,059.4	3.5
secondary forest, 1st degree					
1 year old	10	214,794	6.5	2,147.9	2.5
2 years old	20	161,013	4.9	3,220.3	3.7
3 years old	30	147,174	4.5	4,415.2	5.1
4 years old	40	63,415	1.9	2,536.6	2.9
5 years old	50	126,858	3.8	6,342.9	7.3
6 years old	60	52,003	1.6	3,120.2	3.6
7+ years old	70	229,872	7.0	16,091.1	18.5
total, 1° sec. for.		995,130	30.1	37,874.2	43.6
secondary forest, 2nd degree					
1 years old	5	73,852	2.2	369.3	0.4
2 years old	10	116,017	3.5	1,160.2	1.3
3 years old	15	46,328	1.4	694.9	0.8
4 years old	20	22,673	0.7	453.5	0.5
5 years old	25	59,857	1.8	1,496.4	1.7
total, 2° sec. for.		318,731	9.7	4,174.3	4.8
secondary forest, 3rd degree					
1 years old	5	16,669	0.5	83.3	0.1
2 years old	10	37,230	1.1	372.3	0.4
3 years old	15	9,800	3.0	14.7	~0
total, 3° sec. for.		63,670	1.9	470.3	0.5
secondary forest, 4th degree					
total, 4° sec. for. (1 y.o.)		731	~0	3.7	~0
Total:		3,300,468	100.0	86,798.7	100.0

LIST OF FIGURES



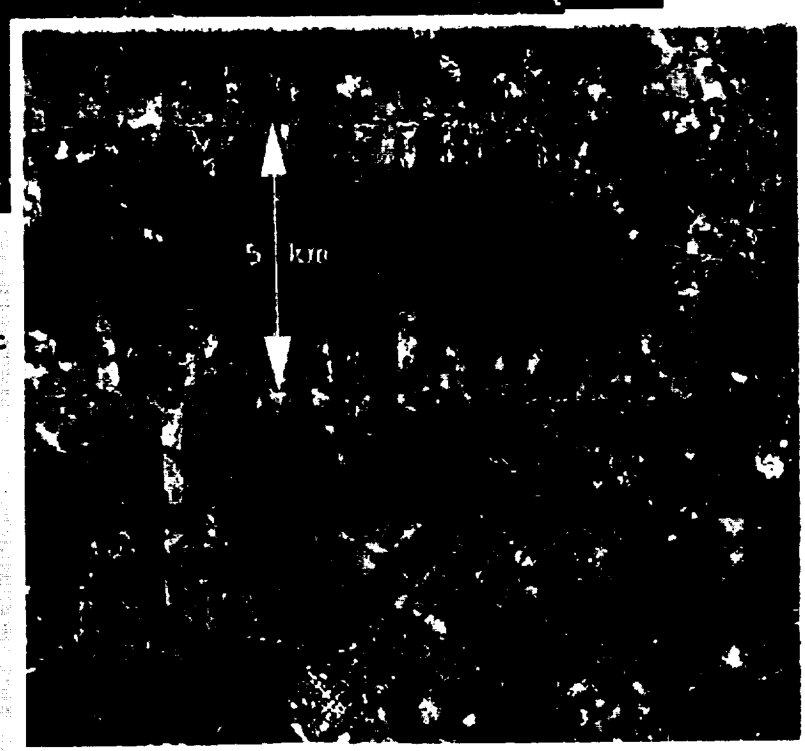
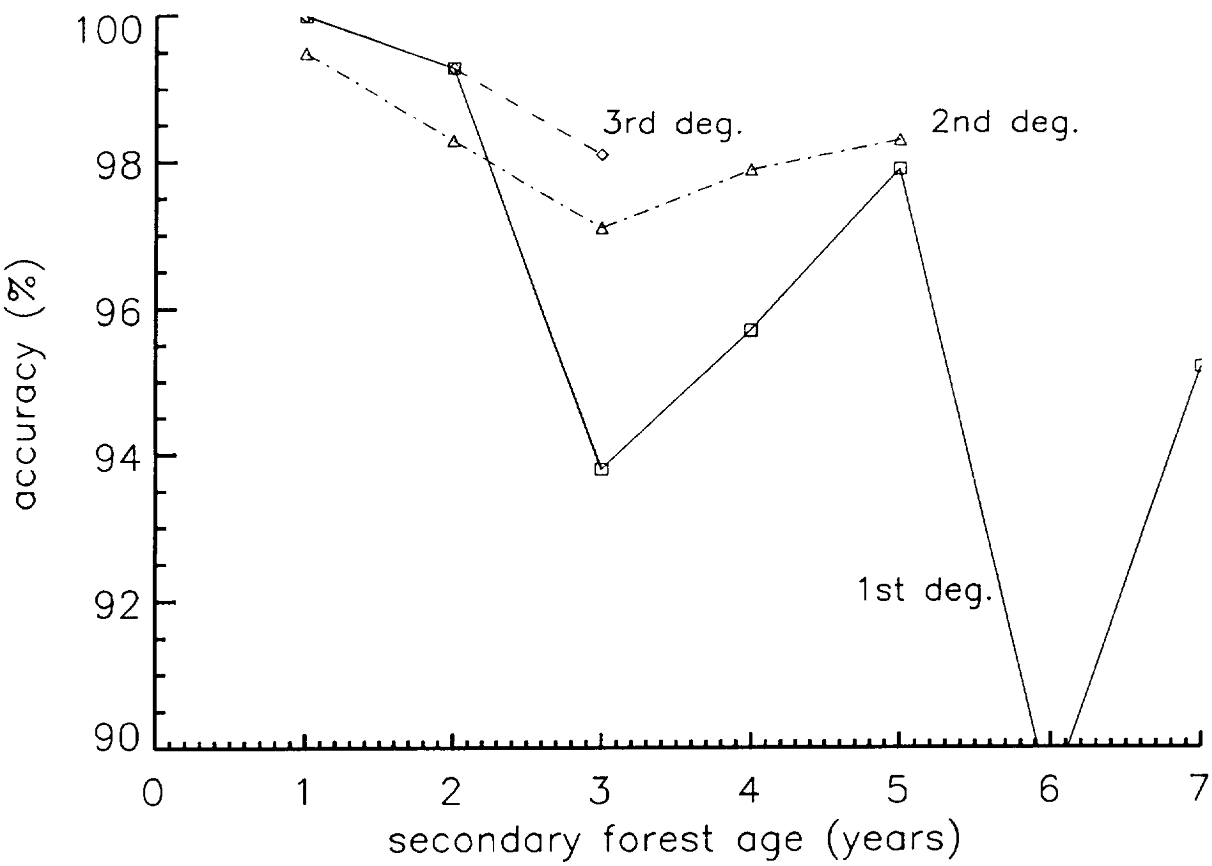
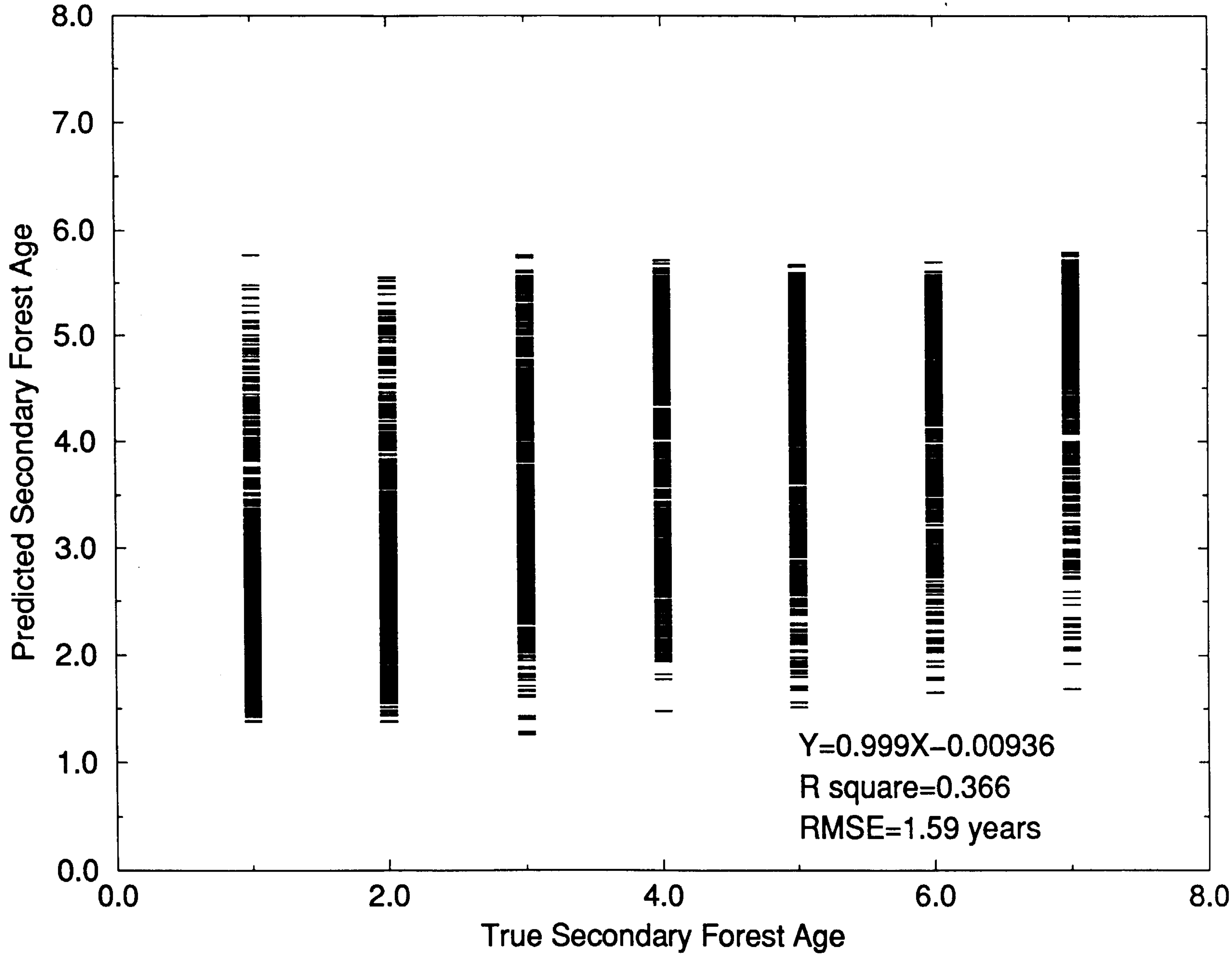
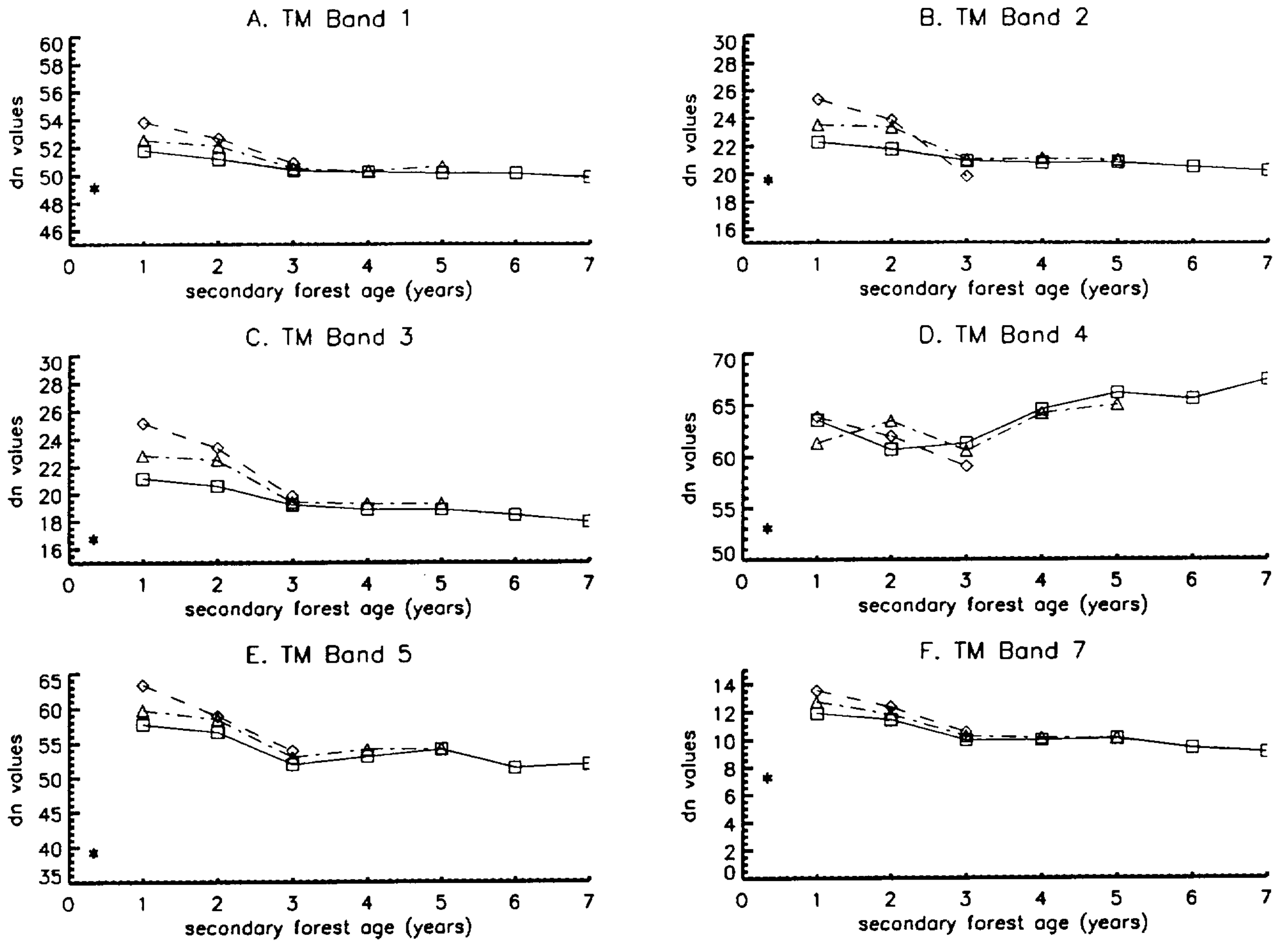


Figure 1. 33,000 km² study area in Rondonia, Brazil; July 25, 1995 TM data. Forest conversion centers on the city of Ariquemes on route BR-364. The polygons in the enlargement identify secondary forest.

red:	1 year old
green:	2 years old
blue:	3 years old
magenta:	4 years old
yellow:	5 years old
aqua:	6 years old
white:	7 years old.


100
98
96
94
92
90
accuracy (%)
0
1
2
3
4
5
6
7
secondary forest age (years)
3rd deg.
2nd deg.
1st deg.


8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
Predicted Secondary Forest Age
Y=0.999X−0.00936
R square=0.366
RMSE=1.59 years
0.0
2.0
4.0
6.0
8.0
True Secondary Forest Age



A. TM Band 1
60
58
56
54
52
50
48
46
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)
B. TM Band 2
30
28
26
24
22
20
18
16
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)
C. TM Band 3
30
28
26
24
22
20
18
16
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)
D. TM Band 4
70
65
60
55
50
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)
E. TM Band 5
65
60
55
50
45
40
35
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)
F. TM Band 7
14
12
10
8
6
4
2
0
dn values
0 1 2 3 4 5 6 7
secondary forest age (years)